

# Metrological Advantages of Applying Vibration Analysis to Pipelines: A Review

Aprovechamiento Metrológico de la Aplicación del Análisis de Vibraciones a Tuberías: Estado del Arte

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Artículo de revisión

**Abstract**— Flow rate is a necessary variable in industrial processes and, therefore, there is a wide variety of instruments designed to measure it. However, the most accepted measuring devices have the problem of being invasive or intrusive. The scientific and technological challenge is to achieve measurement by exploiting all the phenomenological possibilities using a non-intrusive, easy-to-install, portable and low-cost mechanism. This paper presents a literature review on the use of vibration analysis in flow rate metrological systems in order to identify research opportunities for the indirect measurement of this magnitude. The methodology for this review was made up by three stages: revision, analysis and discussion, performed over a wide set of documents published between 2004 and 2020. The analyzed information shows the phenomenological relationship between the features of the vibrations in a pipe and the flow rate magnitude circulating through it, which can be used for metrological purposes. However, several studies report limitations that suggest improvement needs, related to acquisition routines, calibration tests and uncertainty analysis, as well as time-frequency explorations. A promising line of work was found based on soft flow rate sensors that use the analysis of pipeline vibrations integrated into computational intelligence routines, which allows inference of the flow rate value. The findings promote to continue with new technical and scientific challenges.

**Index Terms**— Indirect measurement method, flow rate, soft metrology, soft sensor.

**Resumen**— El caudal es una variable necesaria en procesos industriales, por lo que existe gran variedad de instrumentos para su medición. Sin embargo, las alternativas mejor aceptadas de registro presentan inconvenientes por lo invasivo o intrusivo que requiere ser el medidor para su confiabilidad. El reto científico y tecnológico consiste en lograr la medición explotando todas las posibilidades fenomenológicas mediante un mecanismo no intrusivo, de fácil instalación, portátil y de bajo costo. Este artículo presenta una revisión del estado del arte sobre el uso del análisis de vibraciones en sistemas metrológicos de caudal a fin de identificar oportunidades de investigación para su medición indirecta. La metodología para esta revisión, se compuso de tres etapas: revisión, análisis y discusión, sobre un conjunto amplio de documentos publicados entre 2004 y 2020. La información analizada muestra la relación fenomenológica entre las características de la vibración en una tubería y la magnitud del caudal circulante en ella, lo cual puede ser usado con propósitos

metrológicos. Sin embargo, varios estudios reportan limitaciones que sugieren necesidades de mejoramiento, relacionadas con rutinas de adquisición, pruebas de calibración y análisis de la incertidumbre, así como exploraciones de tiempo-frecuencia. Se encontró una línea de trabajo promisorio basada en soft sensores para caudal que, con el análisis de vibraciones de la tubería integrado a rutinas de inteligencia computacional, permite inferir el valor del caudal. Los hallazgos impulsan a seguir con nuevas apuestas técnico-científicas.

**Palabras claves**— Caudal, método de medición indirecta, soft metrología, soft sensor.

## I. INTRODUCTION

FLOW rate measurement is a relevant issue in many different contexts, such as processes control and potable water distribution networks [1]. Nowadays, there is a wide variety of measuring instruments for this variable that have excellent precision. However, most of these devices have one or several of the following drawbacks: they are intrusive sensors that need to be installed within the pipe [2][3], they require a complex installation procedure that is not suitable for portable measuring systems [1], or they are expensive [4]. These disadvantages are critical in specific applications, such as the contexts where portable measuring systems are required, when a large number of sensors must be installed, or when flow rate is going to be measured in adverse conditions, like in the case of corrosive or very dense fluids

Literature reports new trends in the development of flow rate measurement systems that are easy to install, non-intrusive and not expensive, usually based in the use of soft metrology systems or soft sensors, which are indirect measurement systems that infer the value of the variable of interest from measures of other related variables that are easier to measure [5]. One of the most relevant approaches is the development of flow rate soft metrology systems using the measurement of representational characteristics derived from the vibrations that are produced on a pipe when a fluid is passing through it. This approach has shown promising results to achieve non-invasive and precise flow rate measurement at low cost [6]. Although pipe vibrational analysis has been proposed as a mean to achieve flow rate measurement since the 1990's, this type of

indirect measurement systems is still under development and need to achieve better precision, stability and consistency in the measurement in order to guarantee the reliability of the method.

This paper presents a literature review on the use of pipe vibrational analysis applied to flow rate measurement with the aim of identifying research opportunities in this area. A general structure for this type of system has been identified, along with the main techniques and methods used in the development process, encompassing the sensor selection, the signal processing and the analysis used to infer the flow rate value. Finally, results obtained for different authors in the literature are discussed.

## II. REVIEW METHODOLOGY

The research methodology is qualitative and is made up by three stages, as depicted in Fig. 1.

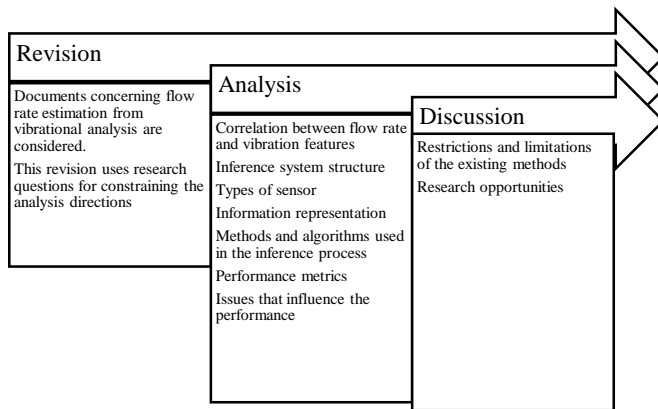


Fig. 1. Stages in the review methodology.

The following sources of information were used: IEEEXplore and SCOPUS. The thesaurus and the number of documents retrieved in each database are shown in Table I.

TABLE I  
REPRESENTATIVE SENSORS IN THE LITERATURE

Keywords	Scopus	IEEEXplore
"flow rate" + "indirect measurement"	96	2
"flow rate" + "soft sensor"	79	5
"flow rate" + "vibration analysis"	260	4
"flow rate" + "soft sensor"	79	15
"flow rate estimation" + "vibration"	7	2
"flow rate" + "accelerometer"	120	18
"flow rate" + "acoustic sensor"	44	4
"flow rate" + LDV	294	5

Several types of documents were retrieved, including journal papers, conferences proceedings and transactions. These documents were further filtered in order to analyze only those that were focused on systems intended to infer a flow rate measurement from vibration analysis. The papers that were considered to be relevant were analyzed in two senses: search for important papers cited and search for those that were

frequently cited by the initial selection.

Because of the subject analyzed in this review is relatively new and the number of papers that directly address the development of flow rate inference based on vibrational features is limited, some papers related to the development of soft sensors, machine learning techniques and sensor characteristics were used to provide context.

The final selection of documents has a time window from 2004 to 2020. These papers were analyzed in the light of the following research questions:

- ¿What features have been proposed for establishing the phenomenological relation between flow rate and pipe vibrations?
- ¿What are the external parameters that influence the relation between flow rate and vibrational features?
- ¿What are the strengths and weaknesses of approaches for the flow rate inference processes from a metrological performance perspective?
- ¿What is the performance of the methods that have used pipe vibrational analysis with metrological purposes and how has this performance been measured?

With these research questions, the documentation of the main developments for flow rate measurement using pipe vibrational analysis were identified. The classification and selection of the information led to the identification of a general structure for flow rate soft sensors, as well as the determination of the most commonly used approaches in each one of the stages that compose such structure. Finally, it was possible to discuss the parameters of influence in flow rate inference models and the strengths, restrictions and limitations. Table II shows the documents that were considered to be the most relevant for the subject of the review.

## III. CONTENT

### A. Flow rate and vibrations

The correlation between vibrations and flow rate on a pipe has been studied since the 1990's, but it is still a field in development and there are not commercial developments yet. In 1992, INEEL (Idaho National Engineering and Environmental Laboratory) performed a series of loss-of-fluid tests that considered several measurements, including an accelerometer attached to the pipe. The measurement analysis revealed that the standard deviation of the signal increased with flow rate. This initial result motivated an additional study, that was fund by the same laboratory and focused in the study of the correlation between vibration and flow rate with metrological purposes [6].

Different alternatives have been proposed in the field of flow rate indirect measurement techniques. In the literature, the experimental correlation between the fluid flow rate through a pipe ( $\dot{Q}$ ) and the acceleration affecting the pipe wall in the radial direction ( $\frac{\partial^2 r_w}{\partial t^2}$ ) has been described with a series of linear relations ( $\alpha$ ), expressed by (1) [4][1].

TABLE II  
MORE RELEVANT DOCUMENTS FOUND REGARDING FLOW RATE ESTIMATION USING VIBRATIONAL ANALYSIS

AÑO	Title	Key words	Data base	Type of publication	DOI
2004	Flow Rate Measurements Using Flow-induced Pipe Vibration [6]	Flow measurement, instrumentation, pipe flow, noise	Scopus	Journal Q1	10.1115/1.1667882
2008	NAWMS: Nonintrusive Autonomous Water Monitoring System [7]	Adaptive sensor calibration, machine learning, water flow rate estimation, nonintrusive and spatially distributed sensing, tiered information architecture, parameter estimation via optimization	Scopus	Conference proceedings	10.1145/1460412.1460443
2011	Initial Test and Design of a Soft Sensor Flow Estimation Using Vibration Measurements [14]	Microphones, frequency domain analysis, fluid flow measurement, estimation, vibrations, pollution measurement, accuracy	IEEE	Conference	10.1109/ICCIAutom.2011.6356765
2013	Fluid Flow Rate Estimation Using Acceleration Sensor [10]	Vibrations measurement, flow rate measurement in pipes, accelerometer, LDV.	IEEE	Conference	10.1109/ICSensT.2013.6727646
2013	A Nonintrusive and Single-Point Infrastructure-Mediated Sensing Approach for Water-Use Activity Recognition [34]	Water-use activity recognition, machine learning, infrastructure-mediated sensing	IEEE	Conference	10.1109/HPCC.and.EU.C.2013.304.
2015	Fluid Flow Measurements by Means of Vibration Monitoring [5]	Flowmeter, acceleration measurement, micro-accelerometer, signal processing, laser Doppler vibrometer	Scopus	Journal Q1	10.1088/0957-0233/26/11/115306.
2015	Correlating Sound and Flow Rate at a Tap [13]	Flow rate, Sound, water use	Scopus	Conference proceedings	doi:10.1016/j.proeng.2015.08.953.
2015	Nonintrusive Method for Measuring Water Flow in Pipes [2]	Flow measurement, pipe vibration, piezoelectric accelerometer.	Scopus	Conference proceedings	
2016	Optimization of Flow Rate Measurement Using Piezoelectric Accelerometers: Application in Water Industry [3]	Second order calibration uncertainty, pipe vibration, flow induced vibration, piezoelectric accelerometer, water flow rate measurement	Scopus	Journal Q1	10.1016/j.measurement.2016.05.101
2018	Vibrational Signal Processing for Characterization of Fluid in Pipes [1]	Fluid flow measurements, flowmeter, vibration measurements, laser Doppler vibrometer, vibration signal processing, fast fourier transform, root mean square value, random signals	Scopus	Journal Q1	10.1016/j.measurement.2017.06.040.
2018	Flow Measurement by Wavelet Packet Analysis of Sound Emissions [12]	Acoustic emissions, flow measurement, fluids, multilayer perceptron, norm entropy, wavelet packet analysis	Scopus	Journal Q4	10.1177/0020294018768340
2018	Estimación of Flow Rate Through Analysis of Pipe Vibration [8]	Accelerometer, estimation, frequency response, flow rate, neural network, vibration	Scopus	Journal Q3	10.2478/ama-2018-0045
2018	Non-invasive Estimation of Domestic Hot Water Usage with Temperature and Vibration Sensors [9]	Hot water flow estimation, Smart water heaters, Smart grid	Scopus	Journal Q2	10.1016/j.flowmeasinst.2018.07.003.
2020	Smart Water Grid: A Smart Methodology to Detect Leaks in Water Distribution Networks [11]	Smart city, smart water grid, vibration measurement, laser Doppler vibrometry, water leaks, smart sensing	Scopus	Journal Q1	10.1016/j.measurement.2019.107260.

$$\dot{Q} = A\bar{U} \propto u' \propto \tau_w \propto \frac{\partial^2 \tau_w}{\partial t^2} \quad (1)$$

Where,  $A$  is the cross-sectional area of the pipe,  $\bar{U}$  is the averaged flow velocity,  $u'$  is the flow velocity fluctuations along axial,  $\tau_w$  is the shear stress in the pipe. In order to establish a direct mathematical relation between vibration and flow rate, in [7], a third order root function of the water flow rate  $f(t)$ , expressed by (2), was successfully tested.

$$f(t) = \alpha^3 \sqrt[3]{v(t)} + \beta \sqrt{v(t)} + \gamma v(t) + \delta \quad (2)$$

Where,  $v(t)$  is the measured vibration, and  $\alpha$ ,  $\beta$ ,  $\gamma$  and  $\delta$  are

function parameters that must be adjusted according to the study case. These relationships given by (1) and (2) have allowed the development of soft sensors that use measurements of pipe vibrational features to infer the value of the flow rate.

Although several studies in the literature use a variety of methodological structures for relating flow rate with vibrations, it is possible to deduce a general structure based on signal processing, the construction of representation spaces and inference by machine learning techniques, as shown in Fig. 2.

### B. Signal acquisition

There are many three types of sensors (see Table III) that have been used to acquire signals that capture the vibrational features

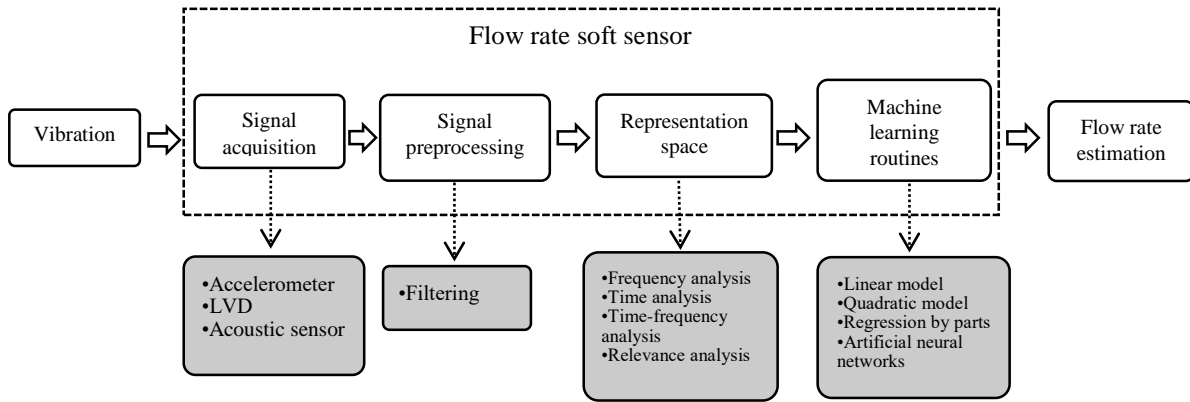


Fig. 2. Flow rate soft sensor structure.

TABLE III  
REPRESENTATIVE SENSORS IN THE LITERATURE

Sensor	Authors
Accelerometer	Evans <i>et al.</i> 2004 [6], Kim <i>et al.</i> 2008 [7], Hu <i>et al.</i> 2013 [34], Medeiros <i>et al.</i> 2016 [3], Venkata & Navada 2018 [8], Pirow <i>et al.</i> 2018 [9].
LVD	Dinardo <i>et al.</i> 2013 [10], Campagna <i>et al.</i> 2015. [4], Dinardo <i>et al.</i> 2018 [1], Fabbiano <i>et al.</i> 2020 [11].
Acoustic sensor	Safary & Travassoli 2011 [14], Kakuta <i>et al.</i> 2012 [15], Jacobs <i>et al.</i> 2015 [13], Goksu 2018 [12]

on a pipe: accelerometers, which are attached to the pipe wall and register the acceleration that affects in in several axes [2] [3] [6] [8] [9] [7]; Laser Doppler Vibrometer (LDV), that use a laser and an interferometer to measure the vibration amplitude and frequency based on the Doppler shift of the laser reflected on the pipe surface [1] [4] [10] [11]; and acoustic sensors, which have been used on works that focus on vibrations associated with acoustic dynamics, where promising results have been accomplished [12] [13] [14] [15].

Accelerometers are popular sensors in vibrational signal acquisition, and have been used in a variety of applications such the integrity analysis of structures and machinery [16] [17], water leak localization [18][19], helicopter transmission diagnostics [20] [21] and detecting incipient damage on rotating machines [22], among others. The fact that accelerometers usually measure the vibrational characteristics in three axes provides a more complete representation of the system dynamics, which allows constructing a better inference space, increasing the soft sensor accuracy [23].

Piezoelectric and MEMS accelerometers have been used in flow rate soft sensors. Piezoelectric accelerometers have low noise levels and wide frequency responses but they are more expensive and they suffer from significant attenuation and phase shifts at low frequencies. Also studies in some piezoelectric accelerometer have shown a noise spectral density that increases with decreasing frequency. In contrast, MEMS accelerometers are less expensive and they exhibit a good response at low frequencies, but they have a smaller bandwidth and present higher noise levels [24][25].

LDVs have been used since 1964 in several different

applications, such as structural health monitoring [26], the analysis of propagation and scattering properties of ultrasonic waves in solids [27] and condition monitoring of wind turbines [28]. One of the advantages of this type of sensor is that the instrument does not require direct contact with the analyzed pipe surface. However, that characteristic may be an inconvenient in the cases where there is limited access or not line of sight [29].

Acoustic sensors have been used in machine and structural monitoring [30], leak detection systems [31], the detection of solid particles in water-conveying pipe flow [32] and biomedical applications [33], among others. Similar to LDV, acoustic sensors do not need to be indirect contact with the measured surface, but in this case line of sight is not necessary.

### C. Signal preprocessing

Before processing the sensor signal to obtain a set of representation features suitable for the inference process, some of the papers in the literature include a previous pre-processing stage. Such stage regards basically with a filtering procedure, to remove interferences and disturbances that the signal may contain, such as noise from the electrical network, measurement devices or the booster pump, in order to reduce the effect of noise on the representation space. In the pre-processing stage implementation, different types of filters have been used, such as Butterworth and “notch comb” digital filters [2] [3], Sallen-Key architectures [8], median filters [34] and Wavelet transform based filters [1], which have demonstrated good performance for this type of signals.

### D. Representation space

After the preprocessing stage, an assemble of signal deconstruction algorithms must be structured trough indexes and transforms that can capture the vibrational dynamics to build a feature space from the sensor signals and allow an estimation space for the inference algorithm. In this aspects, literature shows three approaches:

#### 1) Approaches based on frequency analysis

This approach is based in the idea that the fundamental natural frequency of a pipe containing a flowing fluid decreases as the flow rate increases [6], and thus, some authors have used the

spectrum of the signal as an input to the inference algorithm [8].

Usually, the spectrum of the signal is calculated and analyzed to look for parameters that are related to the flow rate. The main parameter used is the amplitude of the first harmonic of the signal spectrum [1][10][11][13][14], but the central frequency of the first harmonic has been used too [6]. In all the cases in the literature, only one feature has been used to represent the system dynamic and, thus, no relevance analysis has been performed to optimize the representation space.

Some of the authors report that the changes in natural frequency are usually very small, and for this reason a technique based frequency analysis would not work well for small flow rates [6]. This has led to the use of other types of analysis. The frequency analysis approach has been used in systems that use either an LDV or acoustic sensors.

### 2) Approaches based on time analysis

The vibration sound in water-conveying pipe flow can be analyzed as a loudness intensity and characterized in terms of the signal amplitude in the time domain [13]. Also, a statistical parameter can be computed over the time signal and used in the inference process. Some authors have used the standard deviation of the vibrational signal [2] [3] or of the frequency domain average time series signal [6] [9], and some other propose the use of the RMS value of the signal [1] [11] [13]. For the RMS value to be a suitable indicator of the vibrational signal energy, the signal must be time invariant and wide-sense stationary [1]. In the same way as for frequency analysis, the works that have used this approach have developed representations with only one feature. The time analysis approach has been used in systems that use accelerometers or microphones as sensors.

### 3) Approaches based on time-frequency analysis

This approach is based in the use of decomposition techniques that analyze both the time and frequency characteristics of the signals, such as wavelets.

In 2018, Göksu propose the use of Wavelet Packet Analysis (WPA), which has the advantage of enabling the analysis of stationary and non-stationary signals [12]. This is an approach that relies on multiple features to represent the system dynamics and includes a relevance analysis, using norm entropy, to obtain an effective representation space. Using this kind of features, a mean absolute error was of  $3.99E-04 L/s$ .

The time-frequency analysis has been used in systems that use microphones as sensors. Experimental results indicate that wavelet transform is a good candidate for flow measurement by acoustic analysis and there are open issues to improvement by varying window width and wavelet basis function.

### E. Machine learning routines

Once the signal processing has been performed and the representation space has been constructed, the obtained features are used as the input for an inference algorithm that is going to compute the flow rate value. The inference model is usually a machine learning algorithm that can learn the relationship between the features and the flow rate using a labeled data set.

Many of the works have proposed a simple linear mode obtained with least squares fit [1][4][9][10], but some others

TABLE IV  
MACHINE LEARNING TECHNIQUES USED IN FLOW RATE INFERENCE

Technique	Advantages	Disadvantages
Linear regression	<ul style="list-style-type: none"> <li>• Well-known</li> <li>• Low complexity</li> <li>• Good interpretability</li> <li>• Good performance when outputs are linearly independent from inputs</li> <li>• Many real world problems can be simplified</li> </ul>	<ul style="list-style-type: none"> <li>• Can identify only linear relations</li> <li>• Low performance with highly collinear data</li> <li>• Sensitive to outliers</li> <li>• Assumes normally distributed data</li> </ul>
Polynomial regression	<ul style="list-style-type: none"> <li>• Low computational complexity</li> <li>• Very flexible for empirical developments</li> <li>• Broad range of functions can be fit</li> <li>• Polynomial fit a wide range of curvature</li> </ul>	<ul style="list-style-type: none"> <li>• Strong sensitive to outliers</li> <li>• Low performance with highly collinear data</li> <li>• Prone to overfitting</li> <li>• Fewer model validation tools</li> </ul>
Regression by parts	<ul style="list-style-type: none"> <li>• Very flexible</li> <li>• Combines all the strengths of linear and polynomial regression</li> </ul>	<ul style="list-style-type: none"> <li>• Prior knowledge of the nature of the data for a good selection of parts</li> <li>• Sensitive to outliers</li> <li>• Unsuitable for highly collinear data</li> <li>• Prone to overfitting</li> </ul>
ANN	<ul style="list-style-type: none"> <li>• Bypasses the feature selection /extraction stage</li> <li>• Good performance for highly nonlinear processes</li> <li>• High generalization capability</li> <li>• Nonlinear mapping in large datasets</li> <li>• Possibilities for probabilistic assignment</li> <li>• No prior knowledge of the nature of the data</li> </ul>	<ul style="list-style-type: none"> <li>• Training is computationally demanding</li> <li>• Latent probability of overfitting</li> <li>• A lot of parameters to be adjusted</li> <li>• Low performance if the number of descriptors exceeds the number of observations</li> </ul>

have proposed nonlinear models, such as polynomial regression [2] [3][6][14] and a third order square root curve [7]. Also, regression by parts has been used, combining linear and quadratic fits or third degree polynomial regression and quadratic regression [2] [3].

Some other authors have used Artificial Neural Networks (ANN), which can learn more complex nonlinear models [8] [12]. ANN is one of the most popular alternatives in soft metrology systems [5] and soft sensor development and has been used in a variety of applications [35] [36] [37] [38]. However, there is a lot of machine learning algorithms that are commonly used in soft metrology that have not been explored in the case of flow rate estimation, both for linear and not linear regression. Popular linear machine learning approaches in soft metrology are Multiple Linear Regression (MLR) [39] [40] [37] [41], Principal Component Regression (PCR) [37] [42], Partial Least Squares (PLS) [43] [44] [45] [38] [46], Ridge Regression (RR) [77], Least Absolute Shrinkage Selection Operator (LASSO) [40] [47] and Gaussian Process Regression (GPR) [40] [38]. In nonlinear regression, some of the alternatives are Support Vector Regression (SVR) [48], K Nearest Neighbor (KNN) regression [49] and Extreme Learning Machine (ELM) [50] [51].

As for the relationship between the sensor selection and the type of inference model, the works that use LDVs have always proposed linear models while the ones using accelerometers or microphones have proposed different approaches in the inference model. Table IV is a compendium of advantages and disadvantages of the methods that have been used in the literature for flow rate estimation.

Finally, there are some approaches that do not focus on precisely measure flow rate, but only try to identify patterns in the flow rate associated to activities such as bathing or cooking. In this case, the inference model is replaced with a classification algorithm, like Support Vector Machines [34].

#### F. Flow rate estimation

Results reported in the literature, that have been obtained with the implementations described in the previous section, are diverse and the comparison between them implicates high levels of difficulty because the conditions in which each system has been tested are different in terms of magnitudes, installation parameters, equipment characteristics, data acquisition and sampling, among other issues. Concerning these diverse conditions, some authors have proved the influence that certain operation parameters have in each soft sensor model, such as pipe material and diameter [4], sensor placement [14], temporal duration of the analyzed signals [2][3] and the operation characteristics of the mechanism that boost the fluid through the pipe [10].

Campagna *et al* tested the influence of the pipe diameter and found that increasing it causes a decrease in the sensitivity in the relation between the amplitude of the first harmonic of the signal and the flow rate [4]. They also found that another parameter that has an effect in the relationship between vibrations and flow rate is the pipe material, performing tests in PVC and galvanized steel pipes. They found that the vibrational peaks were greater for PVC than for steel pipes with the same diameter and that the sensitivity was greater for PVC pipes than for steel and this effect was more evident for bigger diameters [4]. This last fact was also observed by Evans *et al*, who stated that the slope of the curve in the relation between the standard deviation of the acceleration signal and the flow rate decreased when the density and stiffness of the material were increased [6].

Dinardo *et al* studied a hydraulic system that had a turbo-pump with variable revolution and they performed tests varying the rpm of the pump. They found models with different parameter for each rpm value, which indicates that this variable also has an effect on the relationship between vibration and flow rate [10]. Medeiros *et al* investigated the effect of varying the duration of the analyzed signals, and stated that 10 seconds is the optimum time to estimate flow rate [2][3]. Venkata & Navada performed test with two different fluids: water and sugar solution. Their proposed model was valid for both fluid, with no need for adjusting parameters [8].

Likewise, Safari & Travasoli studied the effect of changing the placement of the sensor and concluded that the position of the sensor changed the type of correlation between flowrate and vibration. They found a quadratic model when the sensor was

placed in the long horizontal pipe and a linear model when it was placed in the pipe knee [14].

Another difficulty in the literature results comparison is that different authors have used different parameters to express the proposed model accuracy. Some authors report results in terms of the statistical parameter  $R^2$  [6], Root Mean Squared Error (RMSE) or mean absolute error [7][12][13], while others do not report measurement accuracy parameters, but concentrate only

TABLE V  
LITERATURE RESULTS

Authors	Results
Evans <i>et al.</i> , 2004 [6]	PVC pipe: $R^2 = 0.997$ Stainless steel pipe: $R^2 = 0.991$ Aluminum pipe : $R^2 = 0.983$
Kim <i>et al.</i> , 2008 [7]	Tested in several pipes. One of the cases had a mean error of 0.0049 L/s with standard deviation of 0.0014 in a 180 s duration experiment. In general, the results gave an estimation error below
Safari & Tavassoli, 2011 [14]	The absolute accuracy is presented as a function of real flowrate, which is approx. between 50 and 300 L/h
Jacobs <i>et al.</i> , 2015 [13]	Mean error of 15%, with 3 of 5 readings with less than 6% error
Medeiros <i>et al.</i> , 2016 [3]	With 10 mV/g accelerometer: $RMSE = 1.65 m^3/h$ With 100 mV/g accelerometer: $RMSE = 1.87 m^3/h$
Dinardo <i>et al.</i> , 2018 [1]	$RMSE = 0.001 L/s$ $R^2 = 0.997$
Göksu, 2018 [12]	98.62% of mean measurement accuracy with 3.99E-4 L/s mean absolute error that corresponds to 1.38% relative error
Venkata & Navada, 2018 [8]	A different error percentage in presented for each flow rate value, with a mean value of 1.24% and a maximum error of 21 L/h
Pirow <i>et al.</i> , 2018 [9]	A figure presents an analysis of error (%) vs. flow rate. Values vary in a wide range, but errors below 10% are reported for the study cases.

on proving that there is a deterministic relation between vibration characteristics and flow rate, and test the effect of some parameters, such as the pipe characteristics [10][4]. Table V shows some results in the literature that report specific performance results.

The studies in the literature do not discriminate the results during the training phase of the model and the posterior validation, and for this reason it is not possible to estimate the generalization ability of the proposed models. Additionally, some of the studies have several measurement points with low statistical sufficiency (3 to 5 instances of analysis).

One of the papers reviewed in the literature presents a proposal regarding the uncertainty estimation for the soft sensor, where they state that the components that must be considered are the uncertainty associated with the regression algorithm and the one associated with the sensors, including the sensor that registers the vibrational characteristics and the flow rate sensor used to obtain the reference values necessary to train the inference algorithm [2] [3].

## IV. CONCLUSIONS

This paper is a literature review of the metrological advantages of applying vibration analysis to the inference of pipeline flow rate, showing that there is a phenomenological relationship between the characteristics of the vibrations in a pipe and the magnitude of the flow circulating through it. This fact suggests that there are important opportunities for the development of new alternatives of soft sensors that support the estimation in flow rate measurement. Consequently, the metrological use of vibrational analysis in pipes opens a door to new research associated to the parameterization, adjustment and installation of the sensor, in relation to signal processing techniques regarding useful vibration dynamics correlated to flow rate change, in addition to linear or nonlinear approaches to inference.

Although most semi-analytical methods are accurate and can be used in static or dynamic nonlinear systems, or where the flow signal is not completely static, the data provided for the analysis is affected by fluctuations, outliers and even erroneous data. Therefore, the development of this type of systems requires that data acquisition be improved, as published papers suggest that the structures and acquisition schemes present notable difficulties in terms of mechanisms that reduce disturbances and noise. Additionally, the literature reviewed showed that the system parameters that influence the measurement estimation require compensation, self-test or calibration procedures to improve the measurement precision and reliability. The difficulty lies in the fact that the variables of external influence affect the estimation in different proportions, and it is not always possible to distinguish all the variables with their influence weights.

As for the construction of the feature space that represents the vibratory dynamics, the different approaches reviewed report restrictions associated with low sensitivity for low flow rate levels and the need for the analyzed signals to be time invariant and stationary, at least in a broad sense. In this sense, it is evident that time-frequency methods have not been widely explored in this context.

The use of soft sensors for the analysis of measurements that are difficult to observe directly, is becoming an important trend in nanotechnology, robotics, analysis of big data and computational intelligence in the context of the fourth industrial revolution. Therefore, it is necessary to define precise, stable and consistent procedures for estimating the measurement, including new ways of estimating uncertainty measures under procedures that use abstract and multivariate representations. The uncertainty analysis in soft sensor is still an open field in the literature where only few studies have been made [5].

## REFERENCES

- [1] G. Dinardo, L. Fabbiano, G. Vacca, and A. Lay-Ekuakille, "Vibrational signal processing for characterization of fluid flows in pipes," *Measurement*, vol. 113, pp. 196–204, 2018, DOI: <https://doi.org/10.1016/j.measurement.2017.06.040>.
- [2] K. Medeiros, C. Barbosa, and E. Oliveira, "Non-intrusive method for measuring water flow rate in pipe," in *XXI IMEKO World Congress "Measurement in Research and Industry"*, Sep. 2015, pp. 44–50.
- [3] K. A. R. Medeiros, F. L. A. de Oliveira, C. R. H. Barbosa, and E. C. de Oliveira, "Optimization of flow rate measurement using piezoelectric accelerometers: Application in water industry," *Measurement*, vol. 91, pp. 576–581, 2016, DOI: <https://doi.org/10.1016/j.measurement.2016.05.101>.
- [4] M. M. Campagna, G. Dinardo, L. Fabbiano, and G. Vacca, "Fluid flow measurements by means of vibration monitoring," *Meas. Sci. Technol.*, vol. 26, no. 11, p. 115306, 2015, DOI: 10.1088/0957-0233/26/11/115306.
- [5] M. Vallejo, C. de la Espriella, J. Gómez-Santamaría, A. F. Ramírez-Barrera, and E. Delgado-Trejos, "Soft metrology based on machine learning: a review," *Meas. Sci. Technol.*, vol. 31, no. 3, p. 32001, 2020, DOI: 10.1088/1361-6501/ab4b39.
- [6] R. P. Evans, J. D. Blotter, and A. G. Stephens, "Flow Rate Measurements Using Flow-Induced Pipe Vibration," *J. Fluids Eng.*, vol. 126, no. 2, pp. 280–285, May 2004, DOI: 10.1115/1.1667882.
- [7] Y. Kim, T. Schmid, Z. Charbiwala, J. Friedman, and M. Srivastava, "NAWMS: Nonintrusive Autonomous Water Monitoring System," in *Proceedings of the 6th ACM Conference on Embedded Networked Sensor Systems, SenSys '08*, Jan. 2008, pp. 309–322, DOI: 10.1145/1460412.1460443.
- [8] S. Venkata and B. Navada, "Estimation of Flow Rate Through Analysis of Pipe Vibration," *Acta Mech. Autom.*, vol. 12, pp. 294–300, Dec. 2018, DOI: 10.2478/ama-2018-0045.
- [9] N. O. Pirow, T. M. Louw, and M. J. Booysen, "Non-invasive estimation of domestic hot water usage with temperature and vibration sensors," *Flow Meas. Instrum.*, vol. 63, pp. 1–7, 2018, DOI: <https://doi.org/10.1016/j.flowmeasinst.2018.07.003>.
- [10] G. Dinardo, L. Fabbiano, and G. Vacca, "Fluid flow rate estimation using acceleration sensors," in *2013 Seventh International Conference on Sensing Technology (ICST)*, 2013, pp. 221–225, DOI: 10.1109/ICSensT.2013.6727646.
- [11] L. Fabbiano, G. Vacca, and G. Dinardo, "Smart water grid: A smart methodology to detect leaks in water distribution networks," *Measurement*, vol. 151, p. 107260, 2020, DOI: <https://doi.org/10.1016/j.measurement.2019.107260>.
- [12] H. Göksu, "Flow Measurement by Wavelet Packet Analysis of Sound Emissions," *Meas. Control*, vol. 51, no. 3–4, pp. 104–112, Apr. 2018, DOI: 10.1177/0020294018768340.
- [13] H. Jacobs, Y. Skibbe, M. Booysen, and C. Makwiza, "Correlating Sound and Flow Rate at a Tap," *Procedia Eng.*, vol. 119, pp. 864–873, 2015, DOI: <https://doi.org/10.1016/j.proeng.2015.08.953>.
- [14] R. Safari and B. Tavassoli, "Initial test and design of a soft sensor for flow estimation using vibration measurements," in *The 2nd International Conference on Control, Instrumentation and Automation*, 2011, pp. 809–814, DOI: 10.1109/ICCIAutom.2011.6356765.
- [15] Hironori Kakuta; Kajiro Watanabe; Yosuke Kurihara, "Development of Vibration Sensor With Wide Frequency Range Based on Condenser Microphone - Estimate System for Water Flow Rate in Water Pipes -," *World Acad. Sci. Eng. Technol.*, vol. 6, no. 10, p. 714, 2012, [Online]. Available: <http://waset.org/publications/8417/development-of-vibration-sensor-with-wide-frequency-range-based-on-condenser-microphone-estimation-system-for-flow-rate-in-water-pipes->.
- [16] A. Sabato, C. Niezrecki, and G. Fortino, "Wireless MEMS-Based Accelerometer Sensor Boards for Structural Vibration Monitoring: A Review," *IEEE Sens. J.*, vol. 17, no. 2, pp. 226–235, 2017, DOI: 10.1109/JSEN.2016.2630008.
- [17] L. Zhu, Y. Fu, R. Chow, B. F. Spencer, J. W. Park, and K. Mechitov, "Development of a high-sensitivity wireless accelerometer for structural health monitoring," *Sensors (Switzerland)*, vol. 18, no. 1, pp. 1–16, 2018, DOI: 10.3390/s18010262.
- [18] D. Shrivani, Y. R. Prajwal, S. B. Prapulla, N. S. G. R. Salanke, G. Shobha, and S. F. Ahmad, "A Machine Learning Approach to Water Leak Localization," in *2019 4th International Conference on Computational Systems and Information Technology for Sustainable Solution (CSITSS)*, 2019, vol. 4, pp. 1–6, DOI: 10.1109/CSITSS47250.2019.9031010.
- [19] S. El-Zahab, E. Mohammed Abdelkader, and T. Zayed, "An accelerometer-based leak detection system," *Mech. Syst. Signal Process.*, vol. 108, pp. 276–291, 2018, DOI: <https://doi.org/10.1016/j.ymsp.2018.02.030>.
- [20] P. D. Samuel and D. J. Pines, "A review of vibration-based techniques for helicopter transmission diagnostics," *J. Sound Vib.*, vol. 282, no. 1, pp. 475–508, 2005, DOI:

- <https://doi.org/10.1016/j.jsv.2004.02.058>.
- [21] L. Zhou, F. Duan, M. Corsar, F. Elasha, and D. Mba, "A study on helicopter main gearbox planetary bearing fault diagnosis," *Appl. Acoust.*, vol. 147, pp. 4–14, 2019, DOI: <https://doi.org/10.1016/j.apacoust.2017.12.004>.
- [22] S. Schmidt, A. Mauricio, P. S. Heyns, and K. C. Gryllias, "A methodology for identifying information rich frequency bands for diagnostics of mechanical components-of-interest under time-varying operating conditions," *Mech. Syst. Signal Process.*, vol. 142, p. 106739, 2020, DOI: <https://doi.org/10.1016/j.ymsp.2020.106739>.
- [23] M. I. M. Ismail *et al.*, "A Review of Vibration Detection Methods Using Accelerometer Sensors for Water Pipeline Leakage," *IEEE Access*, vol. 7, pp. 51965–51981, 2019, DOI: 10.1109/ACCESS.2019.2896302.
- [24] M. Varanis, A. Silva, A. Mereles, and R. Pederiva, "MEMS accelerometers for mechanical vibrations analysis: a comprehensive review with applications," *J. Brazilian Soc. Mech. Sci. Eng.*, vol. 40, no. 11, p. 527, 2018, DOI: 10.1007/s40430-018-1445-5.
- [25] Y.-S. Lu, H.-W. Wang, and S.-H. Liu, "An integrated accelerometer for dynamic motion systems," *Measurement*, vol. 125, pp. 471–475, 2018, DOI: <https://doi.org/10.1016/j.measurement.2018.05.019>.
- [26] M. S. Harb and F.-G. Yuan, "Damage imaging using non-contact air-coupled transducer/laser Doppler vibrometer system," *Struct. Heal. Monit.*, vol. 15, no. 2, pp. 193–203, Mar. 2016, DOI: 10.1177/1475921716636336.
- [27] W. Zuo, Z. Hu, Z. An, and Y. Kong, "LDV-based measurement of 2D dynamic stress fields in transparent solids," *J. Sound Vib.*, vol. 476, p. 115288, 2020, DOI: <https://doi.org/10.1016/j.jsv.2020.115288>.
- [28] A. U. Dilek, A. D. Oguz, F. Satis, Y. D. Gokdel, and M. Ozbek, "Condition monitoring of wind turbine blades and tower via an automated laser scanning system," *Eng. Struct.*, vol. 189, pp. 25–34, 2019, DOI: <https://doi.org/10.1016/j.engstruct.2019.03.065>.
- [29] S. J. Rothberg *et al.*, "An international review of laser Doppler vibrometry: Making light work of vibration measurement," *Opt. Lasers Eng.*, vol. 99, pp. 11–22, 2017, DOI: <https://doi.org/10.1016/j.optlaseng.2016.10.023>.
- [30] D. Rojas and J. Barrett, "A hardware-software WSN platform for machine and structural monitoring," in *2017 28th Irish Signals and Systems Conference (ISSC)*, 2017, pp. 1–6, DOI: 10.1109/ISSC.2017.7983626.
- [31] G. Kousiopoulos, G. Papastavrou, N. Karagiorgos, S. Nikolaidis, and D. Porlidas, "Pipeline Leak Detection in Noisy Environment," in *2019 8th International Conference on Modern Circuits and Systems Technologies (MOCASST)*, 2019, pp. 1–5, DOI: 10.1109/MOCASST.2019.8741673.
- [32] K. Wang *et al.*, "Vibration and acoustic signal characteristics of solid particles carried in sand-water two-phase flows," *Powder Technol.*, vol. 345, pp. 159–168, 2019, DOI: <https://doi.org/10.1016/j.powtec.2018.12.092>.
- [33] N. Dey, A. S. Ashour, W. S. Mohamed, and N. G. Nguyen, "Acoustic Wave Technology," in *Acoustic Sensors for Biomedical Applications*, Cham: Springer, 2019, pp. 21–31.
- [34] L. Hu, Y. Chen, S. Wang, and L. Jia, "A Nonintrusive and Single-Point Infrastructure-Mediated Sensing Approach for Water-Use Activity Recognition," in *2013 IEEE 10th International Conference on High Performance Computing and Communications & 2013 IEEE International Conference on Embedded and Ubiquitous Computing*, 2013, pp. 2120–2126, DOI: 10.1109/HPCC.and.EUC.2013.304.
- [35] F. A. A. Souza, R. Araújo, and J. Mendes, "Review of soft sensor methods for regression applications," *Chemom. Intell. Lab. Syst.*, vol. 152, no. 2016, pp. 69–79, 2016, DOI: 10.1016/j.chemolab.2015.12.011.
- [36] L. Fortuna, S. Graziani, and M. G. Xibilia, "Comparison of Soft-Sensor Design Methods for Industrial Plants Using Small Data Sets," *IEEE Trans. Instrum. Meas.*, vol. 58, no. 8, pp. 2444–2451, 2009, DOI: 10.1109/TIM.2009.2016386.
- [37] D. Slišković, R. Grbić, and Ž. Hocenski, "Methods for Plant Data-Based Process Modeling in Soft-Sensor Development," *Automatika*, vol. 52, no. 4, pp. 306–318, 2011, DOI: 10.1080/00051144.2011.11828430.
- [38] S. A. Lynn, J. Ringwood, and N. MacGearailt, "Global and Local Virtual Metrology Models for a Plasma Etch Process," *IEEE Trans. Semicond. Manuf.*, vol. 25, no. 1, pp. 94–103, 2012, DOI: 10.1109/TSM.2011.2176759.
- [39] T. C. B. de Moraes, D. R. Rodrigues, U. T. de C. P. Souto, and S. G. Lemos, "A simple voltammetric electronic tongue for the analysis of coffee adulterations," *Food Chem.*, vol. 273, no. 2019, pp. 31–38, 2019, DOI: 10.1016/j.foodchem.2018.04.136.
- [40] J. Wan, S. Pampuri, P. G. O'Hara, A. B. Johnston, and S. McLoone, "On Regression Methods for Virtual Metrology in Semiconductor Manufacturing," in *25th IET Irish Signals & Systems Conference 2014 and 2014 China-Ireland International Conference on Information and Communities Technologies (ISSC 2014/CICT 2014)*, 2014, pp. 380–385, DOI: 10.1049/cp.2014.0718.
- [41] S. Lynn, J. Ringwood, E. Ragnoli, S. McLoone, and N. MacGearailt, "Virtual metrology for plasma etch using tool variables," in *2009 IEEE/SEMI Advanced Semiconductor Manufacturing Conference*, 2009, pp. 143–148, DOI: 10.1109/ASMC.2009.5155972.
- [42] B. Lin, B. Recke, J. K. H. Knudsen, and S. B. Jørgensen, "A systematic approach for soft sensor development," *Comput. Chem. Eng.*, vol. 31, no. 5–6, pp. 419–425, 2007, DOI: 10.1016/j.compchemeng.2006.05.030.
- [43] A. A. Khan, J. R. Moyné, and D. M. Tilbury, "Virtual metrology and feedback control for semiconductor manufacturing processes using recursive partial least squares," *J. Process Control*, vol. 18, no. 10, pp. 961–974, 2008, DOI: 10.1016/j.jprocont.2008.04.014.
- [44] D. Wang, L. Jun, and R. Srinivasan, "Data-Driven Soft Sensor Approach for Quality Prediction in a Refining Process," *IEEE Trans. Ind. Informatics*, vol. 6, no. 1, pp. 11–17, Feb. 2010, DOI: 10.1109/TII.2009.2025124.
- [45] Z. Ge and Z. Song, "A comparative study of just-in-time-learning based methods for online soft sensor modeling," *Chemom. Intell. Lab. Syst.*, vol. 104, no. 2, pp. 306–317, 2010, DOI: 10.1016/j.chemolab.2010.09.008.
- [46] T. Saidi, M. Moufid, O. Zaim, N. El Bari, and B. Bouchikhi, "Voltammetric electronic tongue combined with chemometric techniques for direct identification of creatinine level in human urine," *Measurement*, vol. 115, no. 2018, pp. 178–184, 2018, DOI: 10.1016/j.measurement.2017.10.044.
- [47] G. A. Susto, S. Pampuri, A. Schirru, A. Beghi, and G. De Nicolao, "Multi-step virtual metrology for semiconductor manufacturing: A multilevel and regularization methods-based approach," *Comput. Oper. Res.*, vol. 53, no. 2015, pp. 328–337, 2015, DOI: 10.1016/j.cor.2014.05.008.
- [48] K. Popli, V. Maries, A. Afacan, Q. Liu, and V. Prasad, "Development of a vision-based online soft sensor for oil sands flotation using support vector regression and its application in the dynamic monitoring of bitumen extraction," *Can. J. Chem. Eng.*, vol. 96, no. 7, pp. 1532–1540, 2018, DOI: 10.1002/cjce.23164.
- [49] P. Kang, D. Kim, H. Lee, S. Doh, and S. Cho, "Virtual metrology for run-to-run control in semiconductor manufacturing," *Expert Syst. Appl.*, vol. 38, no. 3, pp. 2508–2522, 2011, DOI: 10.1016/j.eswa.2010.08.040.
- [50] L. Puggini and S. McLoone, "Extreme learning machines for virtual metrology and etch rate prediction," in *2015 26th Irish Signals and Systems Conference (ISSC)*, 2015, pp. 1–6, DOI: 10.1109/ISSC.2015.7163771.
- [51] J. Wang, L. Zhu, W. Zhang, and Z. Wei, "Application of the voltammetric electronic tongue based on nanocomposite modified electrodes for identifying rice wines of different geographical origins," *Anal. Chim. Acta*, vol. 1050, no. 2019, pp. 60–70, 2019, DOI: 10.1016/j.aca.2018.11.016.